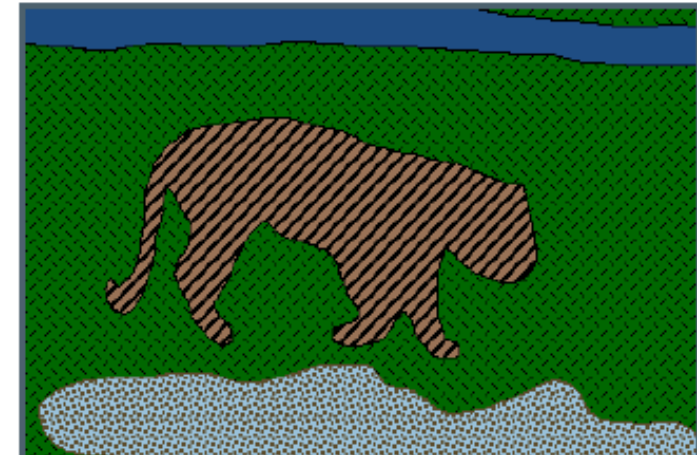


Segmentation

- Image segmentation is the process of partitioning a digital image into multiple parts
- It divide the image into: meaningful and/or perceptually uniform regions
- Segmentation is typically used to locate objects and boundaries of physical entities in the scene
- The segmentation process utilizes available image information (graylevel, colour, texture, pixel position, ...).



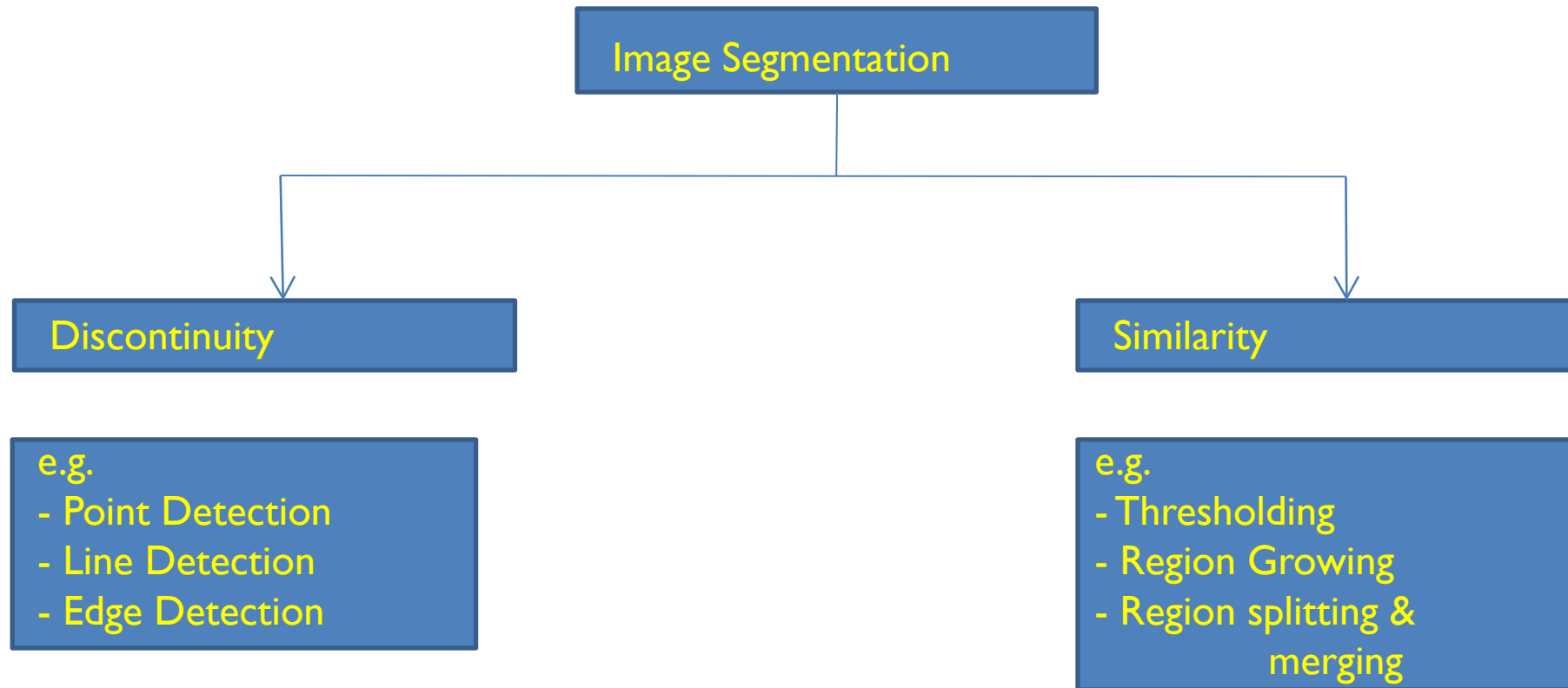
Segmentation methods

Image Segmentation:

- Thresholding techniques
- Clustering methods for segmentation
- Morphological operations

- Active contours (Snakes, Scissors, Level Sets)
- Split and merge (Watershed, Divisive & agglomerative clustering, Graph-based segmentation)
- K-means (parametric clustering)
- Mean shift (non-parametric clustering)
- Normalized cuts
- Graph cuts
- Graylevel thresholding

Classification of the Segmentation techniques



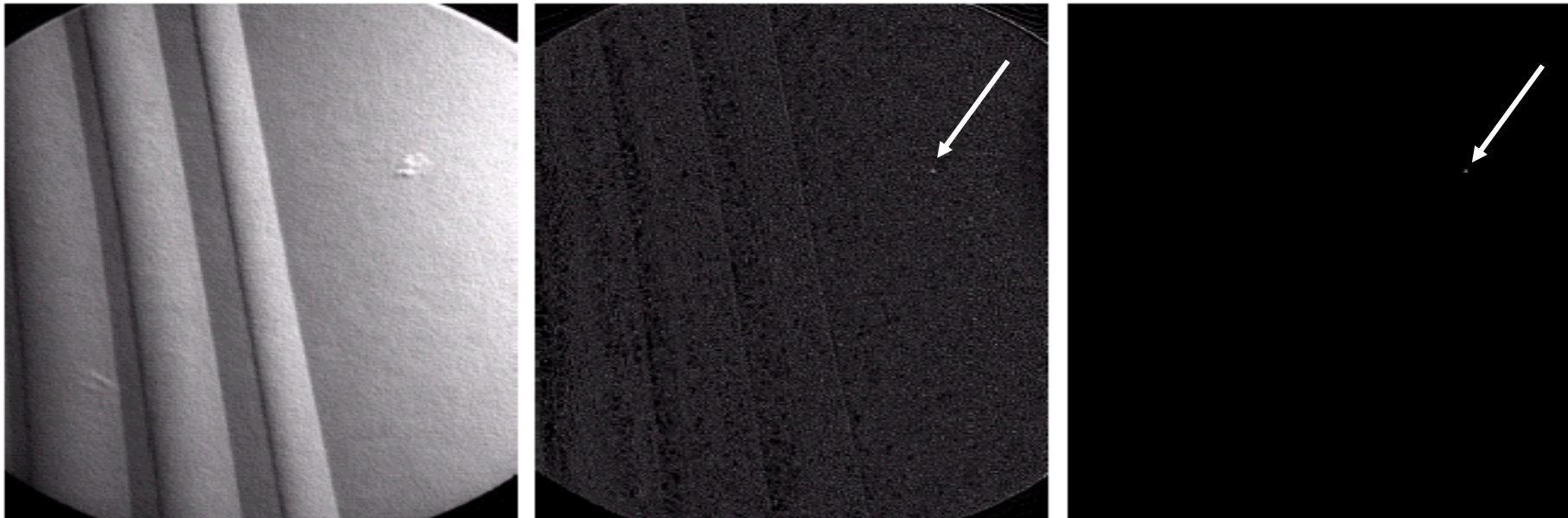
Point Detection

Apply detection mask, followed by threshold detection

-1	-1	-1
-1	8	-1
-1	-1	-1

a
b c d

FIGURE 10.2
(a) Point detection mask.
(b) X-ray image of a turbine blade with a porosity.
(c) Result of point detection.
(d) Result of using Eq. (10.1-2).
(Original image courtesy of X-TEK Systems Ltd.)



Line Detection

-1	-1	-1	-1	-1	2
2	2	2	-1	2	-1
-1	-1	-1	2	-1	-1

Horizontal

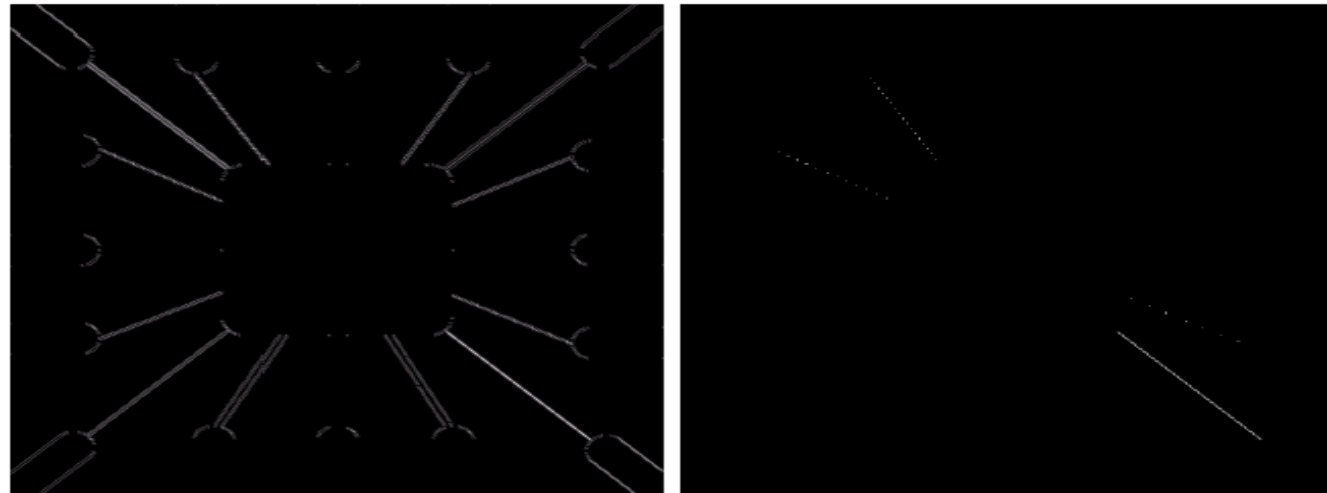
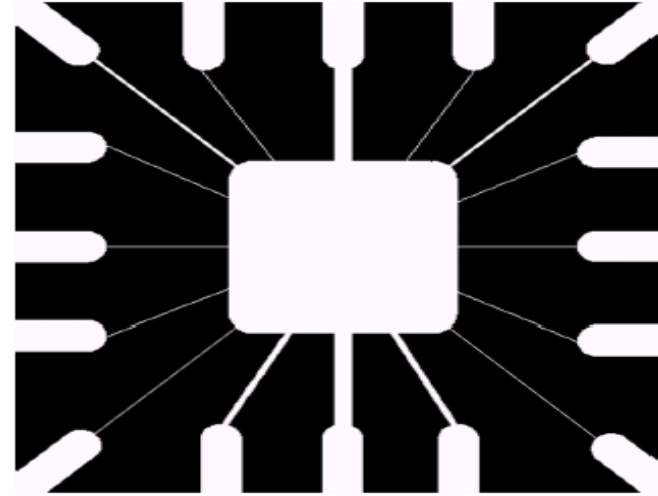
+45°

-1	2	-1	2	-1	-1
-1	2	-1	-1	2	-1
-1	2	-1	-1	-1	2

Vertical

-45°

Useful for detecting lines
with width = 1.



a
b c

FIGURE 10.4
Illustration of line
detection.
(a) Binary wire-
bond mask.
(b) Absolute
value of result
after processing
with -45° line
detector.
(c) Result of
thresholding
image (b).

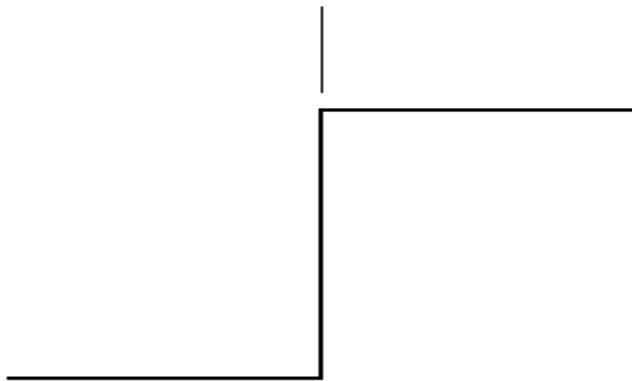
Edge Detection

- Points and lines are special cases of edges.
- Edge detection is difficult since it is not clear what amounts to an edge!

Model of an ideal digital edge



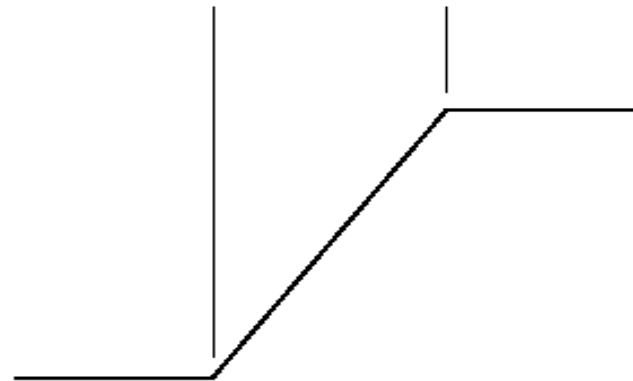
Gray-level profile
of a horizontal line
through the image



Model of a ramp digital edge



Gray-level profile
of a horizontal line
through the image



a b

FIGURE 10.5

(a) Model of an ideal digital edge.
(b) Model of a ramp edge. The slope of the ramp is proportional to the degree of blurring in the edge.

Edge Detection

Robert's Mask

-1	0	0	-1
0	1	1	0

Prewitt Operator

-1	-1	-1	-1	0	1
0	0	0	-1	0	1
1	1	1	-1	0	1

Sobel Operator

-1	-2	-1	-1	0	1
0	0	0	-2	0	2
1	2	1	-1	0	1

Laplacian

-1	-1	-1
-1	8	-1
-1	-1	-1

Combined Detection

- Multimask formulation makes possible development of a method to determine whether a pixel is most likely to be an isolated point or part of a line or an edge.

Boundary Extraction

- Edge detection classifies individual pixels to be on an edge or not.
 - Isolated edge pixels is more likely to be noise rather than a true edge.
 - Adjacent or connected edge pixels should be linked together to form boundary of regions that segment the image.
- Edge linking methods:
 - Local processing
 - Hough transform
 - Graphic theoretic method
 - Dynamic programming

Basic Global Thresholding

1. Select an initial estimate for the global threshold, T .
2. Segment the image using T . It will produce two groups of pixels: $G1$ consisting of all pixels with intensity values $> T$ and $G2$ consisting of pixels with values $\leq T$.
3. Compute the average intensity values $m1$ and $m2$ for the pixels in $G1$ and $G2$, respectively.
4. Compute a new threshold value.

$$T = \frac{1}{2}(m1 + m2)$$

5. Repeat Steps 2 through 4 until the difference between values of T in successive iterations is smaller than a predefined parameter ΔT

Otsu's Algorithm: Summary

1. Compute the normalized histogram of the input image. Denote the components of the histogram by p_i , $i=0, 1, \dots, L-1$.
2. Compute the cumulative sums, $P_1(k)$, for $k = 0, 1, \dots, L-1$.
3. Compute the cumulative means, $m(k)$, for $k = 0, 1, \dots, L-1$.
4. Compute the global intensity mean, $\underline{m}_G$.
5. Compute the between-class variance, for $k = 0, 1, \dots, L-1$.
6. Obtain the Otsu's threshold, k^* .
7. Obtain the separability measure.

Hierarchical clustering

Algorithm of hierarchical agglomeration(built) :

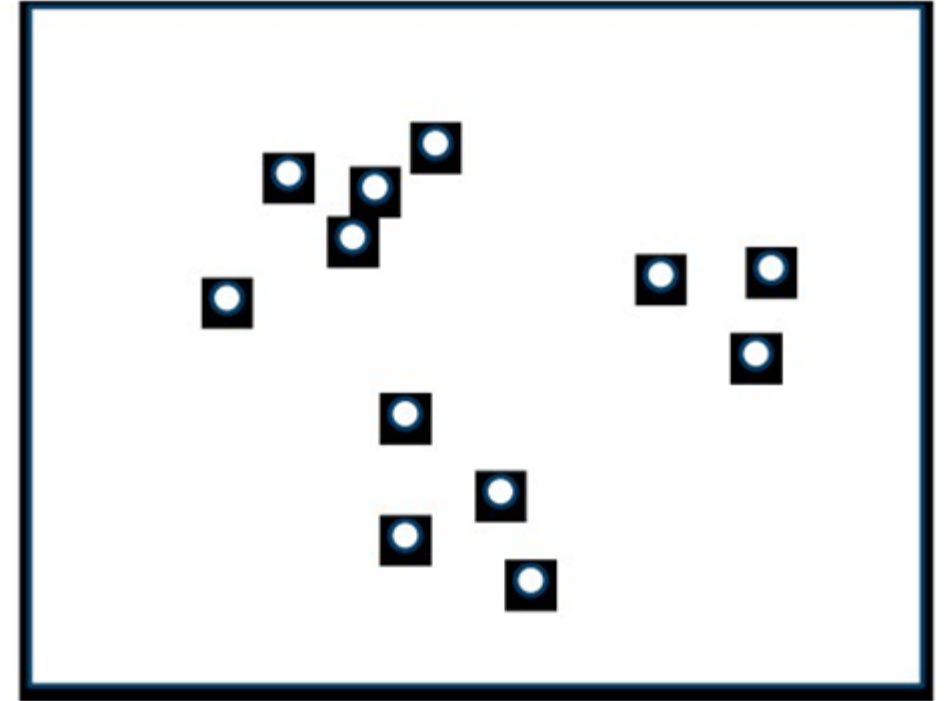
- A. See every single data as a cluster C_i .
- B. Find out C_i , C_j for the distance is the shortest.
- C. Repeat the steps until satisfies our demand.

$d(a,b)$ as the distance between data a and b

- 1) See the whole database as one cluster.
- 2) Find out the cluster having the biggest diameter
- 3) $\max (d(x, c))$, for $\forall x \in C$.
- 4) Split out x as a new cluster C_1 , and see the rest data points as C_i .
- 5) If $d(y, C_i) > d(y, C_1)$, for $\forall y \in C_i$ then split y out of C_i and classify it to C_1
- 6) Back to step2 and continue the algorithm until C_1 and C_i is not change anymore.

K-means (parametric) clustering

1. Select K points (for example randomly) as initial cluster centers
2. Assign each sample to nearest cluster center
3. Compute new cluster centers (i.e. sample means)
4. Repeat steps 2 and 3 until no further re-assignments are possible.



Unlabeled dataset

Mean Shift Algorithm

Mean Shift Algorithm

1. Choose a search window size.
2. Choose the initial location of the search window.
3. Compute the mean location (centroid of the data) in the search window.
4. Center the search window at the mean location computed in Step 3.
5. Repeat Steps 3 and 4 until convergence.

The mean shift algorithm seeks the “mode” or point of highest density of a data distribution:

